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HYPERSPECTRAL IMAGERY CLASSIFICATION USING A BACKPROPAGATION NEURAL NETWORK

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ABSTRACT

A backpropagation neural network was developed and implemented for classifying AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) hyperspectral imagery. It is a fully interconnected linkage of three layers of neural network. Fifty input layer neurons take in signals from Bands 41 to 90 of the AVIRIS spectral data in parallel. Test images are classified into four terrain categories of water, grassland, golf courses and built-up areas using four output neurons. A hidden layer consisting of 12 neurons is used. A training set containing 1,700 pixels for each of the four desired terrain categories is extracted and created from the first test image. Good classification accuracies of 81.8 percent to 95.5 percent are achieved despite the moderate AVIRIS pixel resolution of 20 meters by 20 meters.

INTRODUCTION

The objective is to develop an innovative neural network concept for processing and classifying hyperspectral imagery for potential use in assessing environmental problems, enhancing environmental control and for military applications.

Multiple images of the same region are frequently used to maximize information extraction capability. AVIRIS hyperspectral imagery provides over 200 bands of parallel responses that are not suitable for processing by using conventional single-channel computing devices. The massively parallel nature and adaptability of neural networks have been used to successfuly demonstrate the capability of parallel processing and classsification of AVIRIS imagery, showing the potential for producing timely classification results and analysis of hyperspectral imagery to military or civilian decision-makers.

SELECTION OF INPUT IMAGERY BANDS

AVIRIS provides 224 spectral bands of signals in wavelengths between 400 nm to 2,450 nm. Each band consists of a two-dimensional image of 614 pixels by 512 pixels. Many of these hyperspectral bands cannot be used because of strong absorption from water vapor and carbon dioxide gases [1]. We have two sets of AVIRIS imagery from the Yuma, Arizona and Jasper Ridge, California areas. A Jasper Ridge hyperspectral image was selected for use because it contains more terrain features of interest such as water, grassland, built-up areas and golf courses, while some of these features are absent from the Yuma imagery set. Bands 41 through 90 of this image were chosen as the input to our neural network because their responses are relatively strong, and would provide enough information for the classification of the desired four terrain categories. Due to computer memory size limitations, the band-reduced Jasper Ridge image was further divided into four quarters, and two of the subdivided images were selected as the test images for our neural network. Thus, the final dimensions for the test images are 307 pixels by 256 pixels by 50 bands.

NETWORK IMPLEMENTATION

The neural network used for this research is a fully interconnected linkage with three layered backpropagation as shown in the bottom right portion of Figure 1. It is implemented on a neurocomputer (an HNC neurocoprocessor/SUN4 computer). The input layer consists of 50 neurons which take in signals from Bands 41 to 90 of the AVIRIS spectral data in parallel. Test images are classified into four terrain categories of water, grassland, built-up areas and golf courses using four output neurons. A hidden layer composed of 12 neurons is used for this network. A sigmoid nonlinear activation function is used for each computing neuron in both the output and hidden layers. Besides the input, hidden and output layers, there are four other auxiliary layers of neurons in this network. These auxiliary layers are provided by the HNC neurocoprocessor for the purposes of facilitating network training and performance. They are not shown in Figure 1 for simplicity. A training layer is connected to the output layer in a one-to-one manner. A bias layer containing a single neuron with a constant state of 1.0 is connected to each hidden and output neuron. There is also a layer which computes statistics on the network's performance. The last auxiliary layer is called the class layer which consists of only one neuron. This layer is required only for using the HNC Neurosoft Multilayer Backpropagation Classifier Network (MBC) package [2].

The top portion of Figure 1 shows a test image (or image cube) with respect to the wavelength axis. A very small square shown in white is zoomed and illustrated. An example of pixel responses along the wavelength axis is also shown. Two dotted lines mark that the signal intensities between the center wavelengths 758 nm to 1,230.2 nm (Bands 41 to 90) are distributed among and fed into the 50 input neurons.

NETWORK TRAINING

A training set containing 1,700 pixels for each of the four desired terrain categories was manually extracted from one of the two test images. During the network training, pixels were randomly picked from the training set and fed into the input layer of the network. It takes approximately four hours of continuous training to achieve network convergence. At the end of network training, weights were saved for the classification of hyperspectral imagery.

CLASSIFICATION RESULTS

After training, the network was switched to the classification mode. The images described earlier were used as the test images for evaluating network performance. Figure 2a shows Band 89 of the first test image. The image consists largely of grasslands and built-up areas. A divided highway runs from the top to the bottom in the middle part of the image. A road intersects this highway at the middle to bottom part of the image. One moderately large and a few small lakes and a golf course are on the left side of the image. There are also some patches of trees/forests and some bare soil and rock areas on this image. It takes approximately 15 minutes for the neural network to classify the entire test image. Since a threshold function was added after each output neuron to reject the unlikely pixels for each classified category, a new category called "unclassified" was created for all rejected pixels. The classified results are shown in Figure 2b. Classified pixels are shown in decreasing intensities as water (brightest), golf courses, built-up areas, grassland and unclassified (darkest). Table 1 shows the neural network performance relative to ground truth for the first test image. The unclassified pixels in the original image belong to other terrain categories not considered in this work.

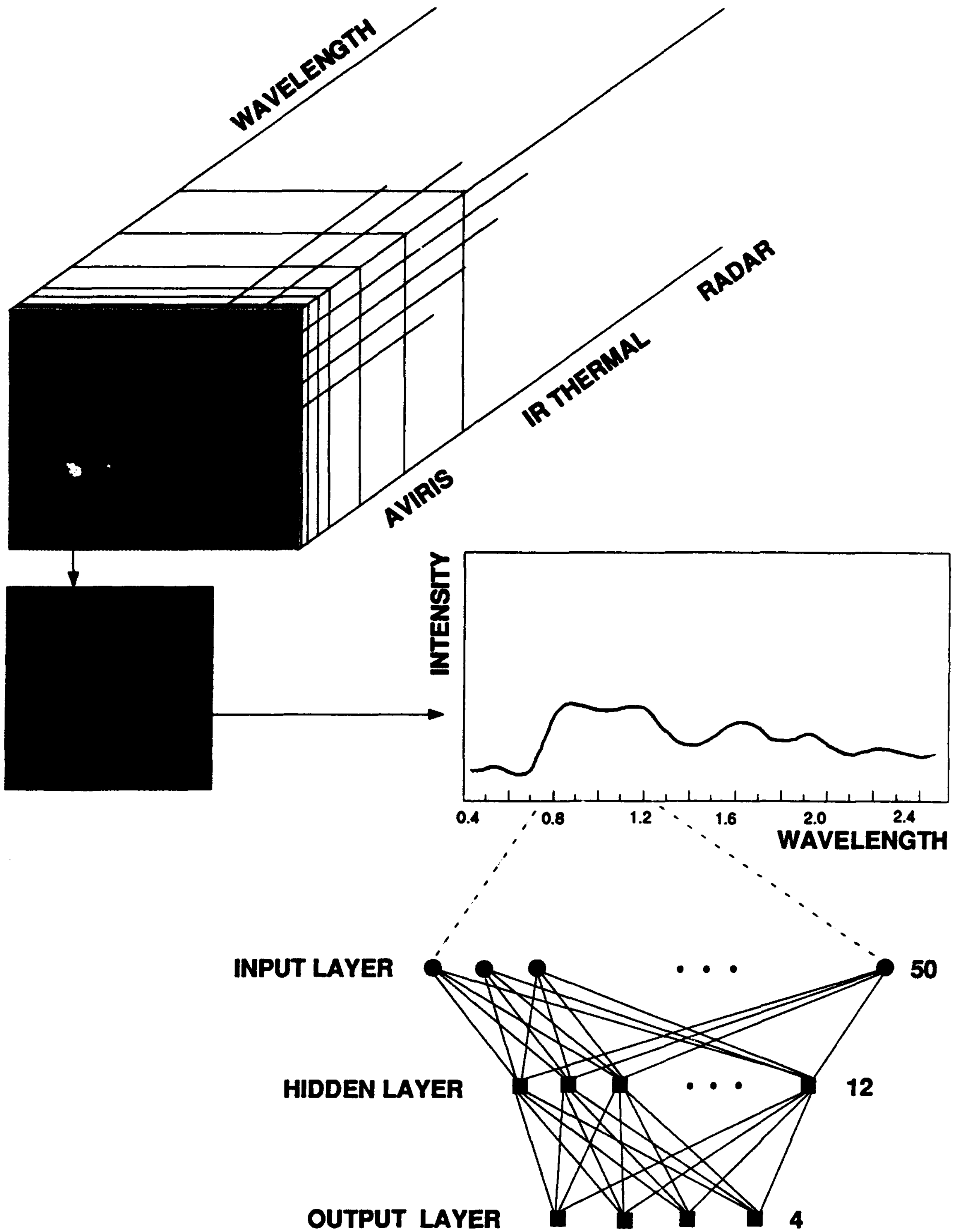

Figure 1. Test Image Cube and Neural Network Configuration

Figure 2a. Band 89 of the First Test Image.

Figure 2b. Classified Results for the First Test Image.

Good classification accuracies of 86.6 percent to 95.5 percent are obtained for all four terrain categories.

TABLE 1: Neural Network Performance Relative to Ground Truth for First Image

Terrain Category	Original Pixels	Classified Pixels	Ratio
Water	594	622	0.955
Built-up Areas	40,056	34,689	0.866
Grassland	34,379	39,152	0.878
Golf Courses	630	714	0.882
Unclassified	2,933	3,415	0.858

The second test image was classified in the same way as the first test image. Figure 3a shows Band 89 of this test image. Similar to the first test image, this image contains largely built-up areas and grasslands. Several roads are clearly visible. Two golf courses were found. In addition, a linear accelerator was located in the upper left quarter of the image. The classified results are illustrated in Figure 3b. Again, it is classified as four terrain categories plus a rejected "unclassified" class. The intensity distribution of the classified pixels are the same as described for the first test image. Table 2 summarizes the neural network performance relative to ground truth for the second test images. There is no water in this image, however, good classification accuracies of 81.5 percent to 93.5 percent are obtained for the rest of the three terrain categories. There are seven pixels misclassified as water although there is no water in this image.

TABLE 2: Neural Network Performance Relative to Ground Truth for Second Image

Terrain Category	Original Pixels	Classified Pixels	Ratio
Water	0	7	Not Applicable
Built-up Areas	48,181	42,860	0.889
Grassland	26,975	28,825	0.935
Golf Courses	2,611	2,130	0.815
Unclassified	825	4,770	0.172

Overall, we have obtained good classification accuracies of 81.5 percent to 95.5 percent for the four desired terrain categories despite the moderate AVIRIS pixel resolution of 20 meters by 20 meters. Improved classification accuracies may be achievable if the images are classified into more categories.

CONCLUSIONS

1. A backpropagation neural network can be effectively trained to classify the large volume AVIRIS image data successfully in parallel.

2. A neural network can be used to classify the AVIRIS hyperspectral imagery with a high classification accuracy despite the moderate pixel resolution.

REFERENCES

[1] Chen, H. S. and Try, P. D., "Atmospheric Effects on Hyperspectral Remote Sensing of the Land Surface," STC Technical Report 2590, March 1992.

[2] HNC User Interface Subroutine Library (UISL) Reference Guide, March 1991.

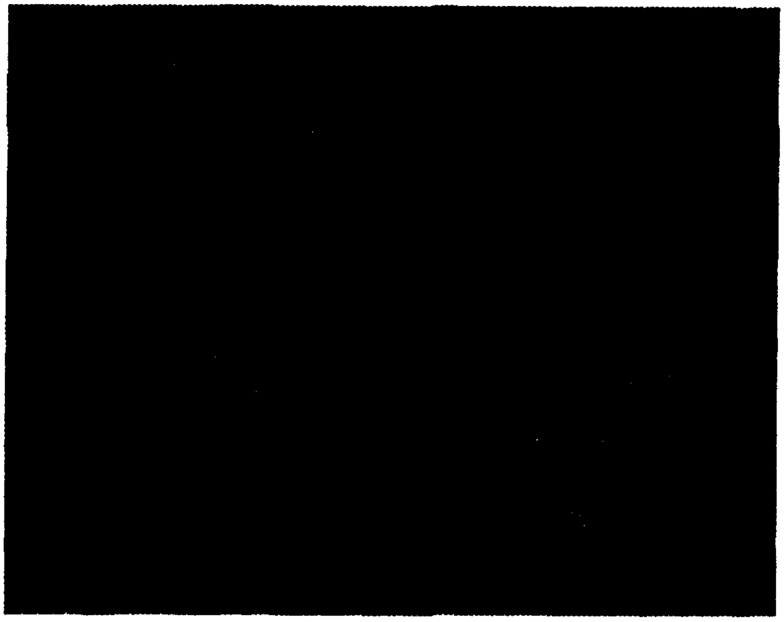

Figure 3a. Band 89 of the Second Test Image.

Figure 3b. Classified Results for the Second Test Image.